#### **Course #412**

#### Analyzing Microarray Data using the mAdb System

February 16-17, 2005 1:00 pm - 4:00pm madb-support@bimas.cit.nih.gov

- Intended for users of the mAdb system who are familiar with mAdb basics
- Focus on analysis of multiple array experiments

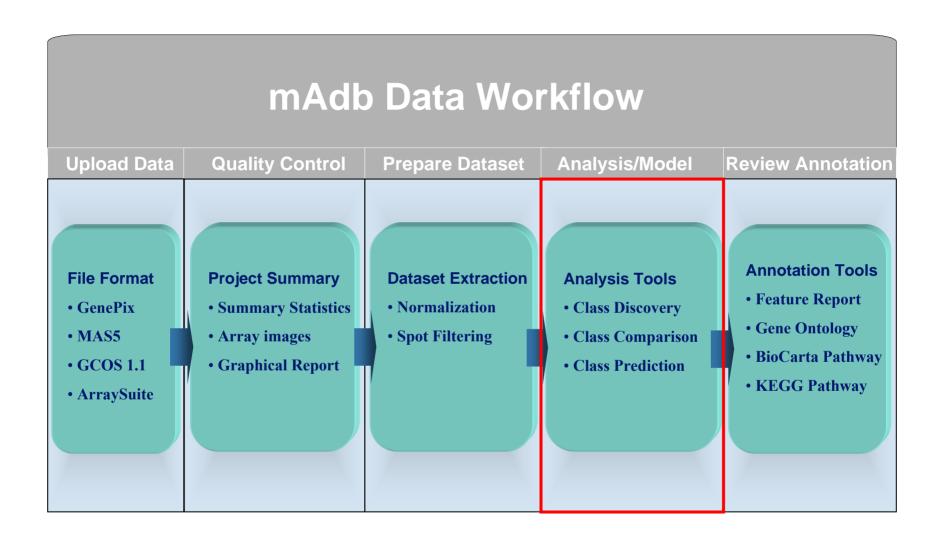
Esther Asaki, Liming Yang, John Powell

#### Agenda

- 1. mAdb system overview
- 2. mAdb dataset overview
- 3. mAdb analysis tools for dataset
  - Class Discovery clustering, PCA, MDS
  - Class Comparison statistical analysis
    - t-test
    - ANOVA
    - Significance Analysis of Microarrays SAM
  - Class Prediction PAM

Various Hands-on exercises

## 1. mAdb system overview



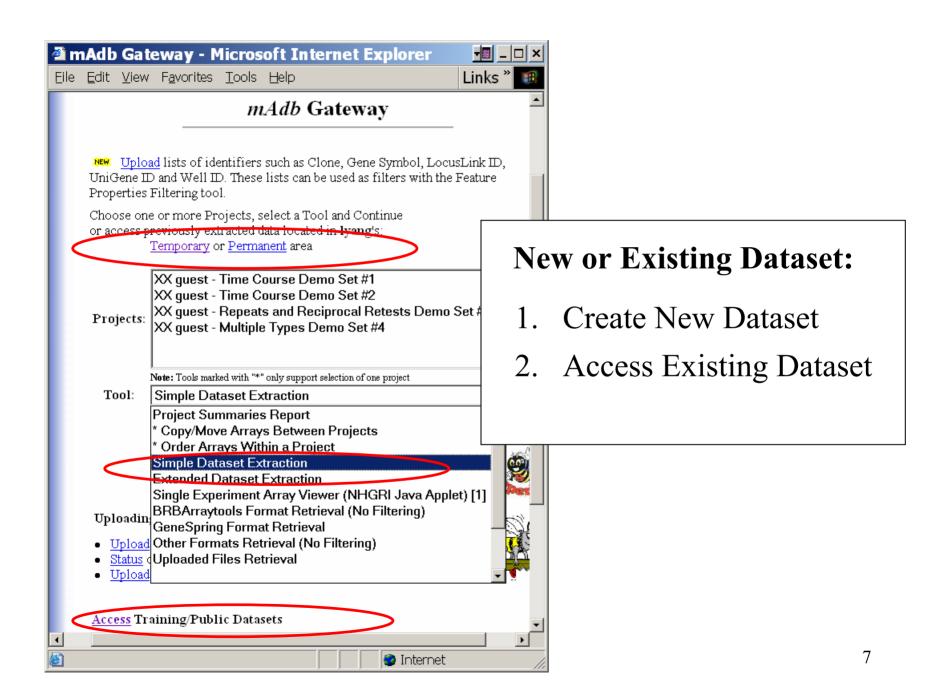
#### 2. mAdb dataset overview

#### What is a dataset?

- mAdb Dataset
  - Collection of data from multiple experiments
  - Genes as rows and experiments as columns

		sample1	sample2	sample3	sample4	sample5	
	1	0.46	0.30	0.80	1.51	0.90	
	2	-0.10	0.49	0.24	0.06	0.46	
Genes	3	0.15	0.74	0.04	0.10	0.20	
	4	-0.45	-1.03	-0.79	-0.56	-0.32	
	5	-0.06	1.06	1.35	1.09	-1.09	

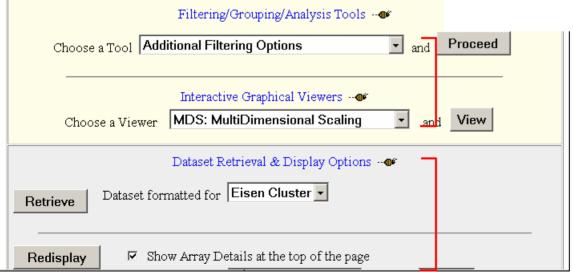
Gene expression level = (normalized) Log(Red signal / Green signal)



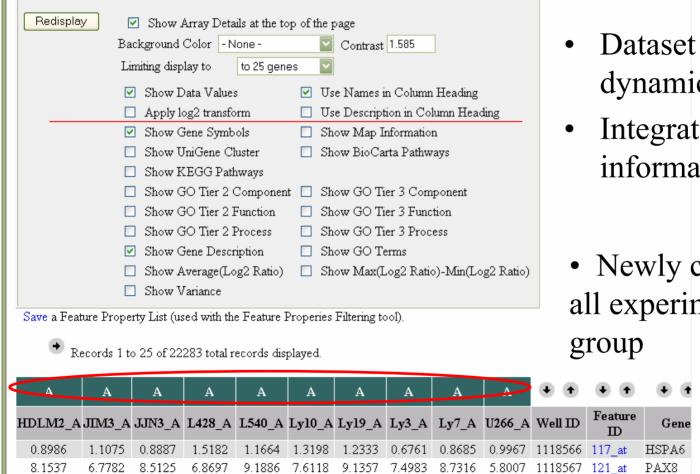
#### A 0.008 1. HDLM2 A HL HDLM2 MM JIM3 A 0.007 2. JIM3 A A 0.007 3. JJN3 A MM JJN3 A 0.006 4. L428 A HL L428 HL L540 A 0.009 5, L540 A DLBCL Lv10 A 0.006 6. Lv10 A DLBCL Lv19 A 0.007 7. Lv19 A A 0.007 8. Lv3 A DLBCL Lv3 A 0.007 9. Ly7 A DLBCL Ly7 A 0.007 10. U266 A MM U266 Edit Data for Dataset: Cell Lines representing 3 Lymphomas 10 Arrays and 22283 Expression Rows extracted. Data transformation method: Centered to Signal Median Spot Filter Options: Signals are floored at 100.0 Expand this Dataset. Access Datasets in your Temporary area. Filtering/Grouping/Analysis Tools -- @

#### **Dataset Display Page**

- Dataset History
- Analysis Tools
- Retrieval and Display Options...



#### **Dataset Display**



- Dataset display options dynamic
- Integrated gene information

 Newly created dataset puts all experiments into a single

#### mAdb Dataset Display

E74-like factor 4 (ets domain transcripti-

1118594 31861 at IGHMBP2 immunoglobulin mu binding protein 2

Group label	A	A	A	A	A	• •	• •	• •	• •
Sample name	BJAB_A_B	Daudi_A_B	Jurkat_A_B	Ly10_A_B	Ly3_A_B	Well ID	Feature ID	Gene	Description
				7.7702		1118566	117_at	HSPA6	heat shock 70kDa protein 6 (HSP70B')
	9.7305	9.7985	9.7249	10.2981	10.1150	1118567	121_at	PAX8	paired box gene 8
		8.9715				1118568	177_at	PLD1	phospholipase D1, phophatidylcholine-sp
		8.8918	9.0752	10.2200		1118569	179_at	PMS2L9	postmeiotic segregation increased 2-like
	8.4250	7.0224	7.8511	7.4692	7.7886	1118570	320_at	PEX6	peroxisomal biogenesis factor 6
	6.9189	7.5645			7.7814	1118572	564_at	GNA11	guanine nucleotide binding protein (G pro
	9.3296	9.6202	9.4409	9.9652	10.0534	1118573	632_at	GSK3A	glycogen synthase kinase 3 alpha
				7.8629	7.3505	1118574	823_at	CX3CL1	chemokine (C-X3-C motif) ligand 1
	10.0053	9.6605	9.3872	9.9003	9.3181	1118575	1053_at	RFC2	replication factor C (activator 1) 2, 40kD
genes	8.1908	8.2187	7.3540	8.3650		1118576	1294_at	UBE1L	ubiquitin-activating enzyme E1-like
genes	6.5014			7.0629		1118577	1316_at	THRA	thyroid hormone receptor, alpha (erythro
		6.5251	6.4512			1118579	1431_at	CYP2E1	cytochrome P450, family 2, subfamily E
	9.6604	10.0402	8.6991	9.9747	9.4539	1118581	1487_at	ESRRA	estrogen-related receptor alpha
	8.3781	8.8981	8.1739	8.2322	9.3807	1118582	1729_at	TRADD	TNFRSF1A-associated via death domain
	7.9419	7.4741	7.9301			1118584	1861_at	BAD	BCL2-antagonist of cell death
	8.9372	9.8243	9.4774	9.7465	10.2738	1118585	243_g_at	MAP4	microtubule-associated protein 4
	8.2002			9.9105	9.6255	1118586	266_s_at	CD24	CD24 antigen (small cell lung carcinoma
	5.0575	6.8163	5.9542		5.7388	1118587	31799_at		Sapiens clone 24627 mRNA sequence
	9.9564	9.8420	9.7677	10.1529	9.3419	1118588	31807_at	DDX49	DEAD (Asp-Glu-Ala-Asp) box polypepti
	9.9284	9.6363	9.3726	9.8858	10.1808	1118589	31826_at	KIAA0674	KIAA0674 protein
	9.4419	9.0507	9.4075	9.9434	9.0739	1118591	31837_at	BC002942	hypothetical protein BC002942

10.1029

9.6770

10.5434

9.3613

1118592 31845 at ELF4

9.7502

9.3452

9.2389

9.3869

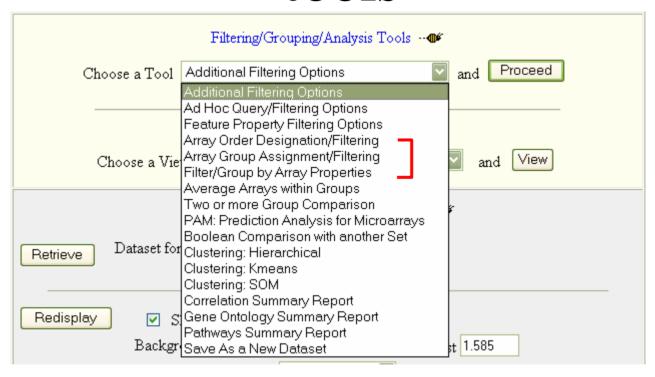
10.4035

9.0906

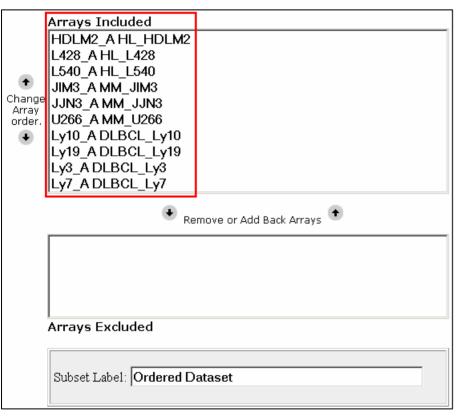
#### Dataset Group Assignment

- Array Order Designation/Filtering
- Array Group Assignment/Filtering
- Filter/Group by Array Properties

# Dataset group assignment tools



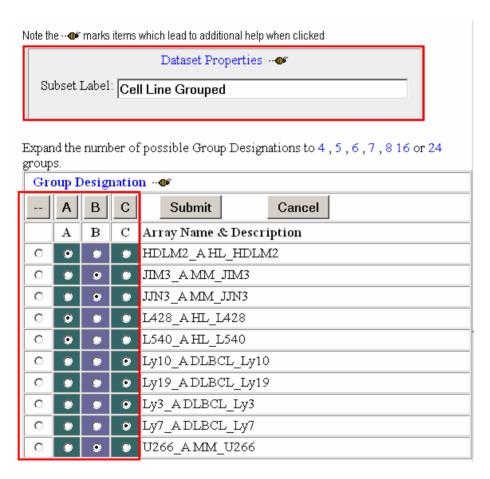
#### **Array Order Designation/Filtering**



- Order arrays in dataset
- Delete/Add back arrays in dataset
- Subsequent analysis will be ordered by groups first and then ordered within each group

Does not group arrays

#### **Array Group Assignment/Filtering**



- One click per array for additional group
- Not convenient for large dataset
- Can not order within group

#### Filter/Group by Array Properties

#### mAdb Dataset Display

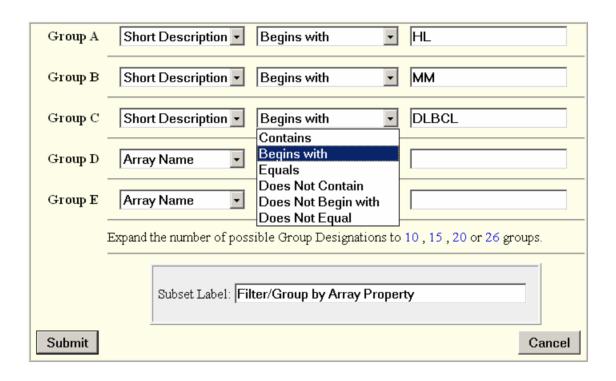
```
A 0.008 1. HDLM2 A HL HDLM2
                   мм лмз
A 0.007 2. JIM3 A
                   MM JJN3
A 0.007 3. JJN3 A
A 0.006 4. L428 A
                   HL L428
                   HL L540
A 0.009 5. L540 A
                  DLBCL Ly10
A 0.006 6. Ly10 A
A 0.007 7. Ly19 A
                  DLBCL Lv19
A 0.007 8. Ly3 A
                   DLBCL Ly3
A 0.007 9. Ly7 A
                   DLBCL Ly7
A 0.007 10. U266 A
                  MM U266
```

Edit Data for Dataset: Cell Lines representing 3 Lymphomas

```
10 Arrays and 22283 Expression Rows extracted.
Data transformation method: Centered to Signal Median Spot Filter Options:
Signals are floored at 100.0
```

- Array properties include Name and Short Description
- Identify consistent pattern

#### Filter/Group by Array Properties



- Convenient for large dataset
- Can not order arrays within group

# **Group Assignment**

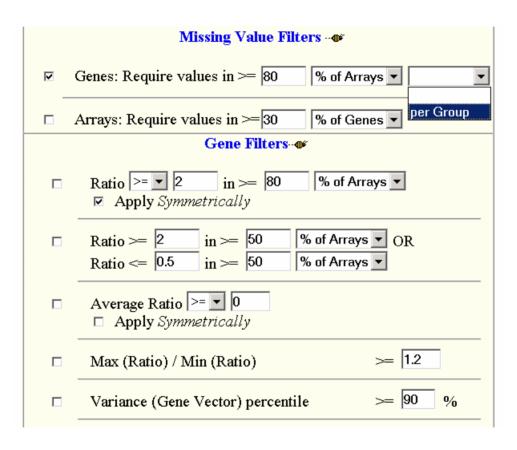
A	A	A	В	В	В	С	С	С	6	• •	• •	• •
HDLM2_A	L428_A	L540_A	JIM3_A	JJN3_A	U266_A	Ly3_A	Ly7_A	Ly10_A	L719_A	Well ID	Feature ID	Gene
0.8986	1.5182	1.1664	1.1075	0.8887	0.9967	0.6761	0.8685	1.3198	1.2333	1118566	117_at	HSPA6
8.1537	6.8697	9.1886	6.7782	8.5125	5.8007	7.4983	8.7316	7.6118	9.1357	1118567	121_at	PAX8
0.8042	2.2147	0.8831	0.6680	0.6954	1.4118	0.6761	0.6743	0.6046	0.7337	1118568	177_at	PLD1
4.1856	6.4728	9.8080	5.3601	6.0779	5.1954	7.1981	3.7505	7.2110	4.8481	1118569	179_at	PMS2L9
2.3557	1.6427	1.2628	2.5865	2.4068	2.0954	1.4949	2.1160	1.0713	2.5561	1118570	320_at	PEX6
1.1856	1.3852	0.9514	0.9599	0.9757	0.8588	1.2529	1.4626	1.3452	1.2318	1118571	336_at	TBXA2R
3.7746	1.6271	2.5043	1.1516	1.0508	0.6536	1.4875	1.9670	1.1227	1.1988	1118572	564_at	GNA11
4.5008	5.1783	5.5333	5.3079	7.4172	6.8863	7.1846	5.8658	6.0435	8.4519	1118573	632_at	GSK3A
4.1646	12.1329	0.8532	0.6680	0.6954	0.6536	1.1034	0.6743	1.4075	0.7337	1118574	823_at	CX3CL1
5.5663	4.3223	5.4480	1.6206	2.9270	4.4418	4.3158	3.3790	5.7775	3.3067	1118575	1053_at	RFC2
3.9173	2.4157	2.0461	1.3460	0.9437	1.1039	1.3083	2.0964	1.9933	1.9391	1118576	1294_at	UBE1L
0.7800	0.7918	0.8532	0.7715	0.6954	0.8327	0.6761	0.8483	0.8083	0.7630	1118577	1316_at	THRA
0.7800	0.6485	0.8532	0.6680	0.6954	0.6536	0.6761	0.6743	0.6046	0.7337	1118578	1320_at	PTPN21

- Group assignment information is carried into relevant analysis
- Dataset is independent from microarray platforms

#### Examples for using group labels

- Additional Filtering per Group
- Correlation Summary Report
- Average Arrays within Groups

#### Filter by Group Properties

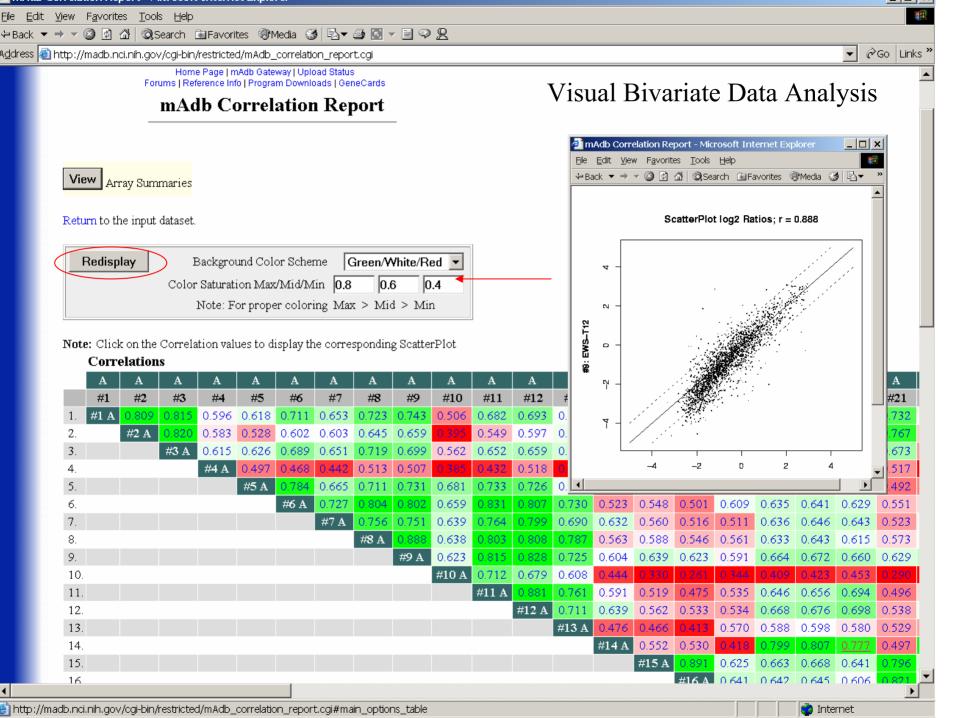


• Ensures each group has sufficient number of non-missing values

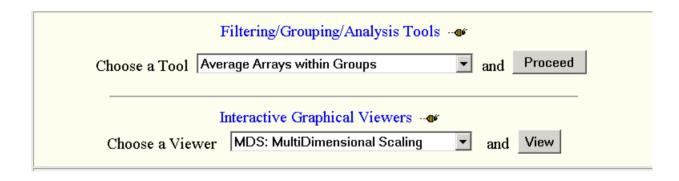
#### **Correlation Summary Report**

Correlations													
A	A	A	В	В	В	С	С	С	С				
#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	Grp		Array Name	Array Description
#1 A	0.890	0.914	0.844	0.873	0.852	0.853	0.838	0.856	0.836	A	<b>II</b> 🔼 1.	HDLM2_A	HL_HDLM2
	#2 A	0.882	0.852	0.860	0.847	0.856	0.824	0.869	0.845	A	🚨 🔼 2.	L428_A	HL_L428
		#3 A	0.860	0.880	0.855	0.858	0.850	0.859	0.843	A	■ 🗓 3.	L540_A	HL_L540
			#4 B	0.896	0.895	0.852	0.826	0.850	0.846	В	🔳 🔼 4.	ЛМ3_А	мм_лмз
				#5 B	0.885	0.868	0.853	0.859	0.867	В	💹 🔼 5.	JJN3_A	MM_JJN3
					#6 B	0.857	0.832	0.852	0.848	В	💹 🔼 6.	U266_A	MM_U266
						#7 C	0.871	0.924	0.882	С	💹 🔼 7.	Ly10_A	DLBCL_Ly10
							#8 C	0.873	0.918	С	💹 🔼 8.	Ly19_A	DLBCL_Ly19
								#9 C	0.883	С	■ 🗓 9.	Ly3_A	DLBCL_Ly3
									#10 C	С	<b>II</b> 10.	Ly7_A	DLBCL_Ly7

- Pair wise correlation between 2 samples in dataset
- Individual scatter plot available
- Group pattern for quality control



#### Average Arrays within Group



 Averages using log ratios - though user chooses to display linear or log2 values

# Dataset I Small Round Blue Cell Tumors (SRBCTs)

- Khan et al. *Nature Medicine* 2001
- 4 tumor classifications
- 63 training samples, 25 testing samples, 2308 genes
- Neural network approach

#### **Hands-on Session 1**

- Lab 1- Lab 4
- Read the questions before starting, then answer them in the lab.
- Use web site: <a href="http://mAdb-training.cit.nih.gov">http://mAdb-training.cit.nih.gov</a>
- Avoid maximizing web browser to full screen.
- Total time: 20 minutes

#### 3. mAdb dataset analysis tools

- Class Discovery: clustering, PCA, MDS
- Class Comparison: statistical analysis
- Class Prediction: PAM

# **Analysis Overview**

Class Discovery - Unsupervised	<ul> <li>Clustering – Hierarchical, K-means, SOMs</li> <li>Principal components Analysis (PCA)</li> <li>Multidimensional Scaling (MDS)</li> </ul>
Class Comparison - Supervised	<ul> <li>paired t-tests</li> <li>t-test pooled (equal) variance</li> <li>t-test separate (unequal) variance</li> <li>Significance Analysis of Micro- arrays (SAM)</li> <li>One way ANOVA</li> <li>Wilcoxon Rank-Sum (Mann Whitney U)</li> <li>Wilcoxon Matched-pairs Signed Rank</li> <li>Kruskal-Wallis</li> </ul>
Class Prediction - Supervised	Prediction Analysis for Microarrays (PAM)

## Class Discovery Example

- Discover cancer subtypes by gene expression profiles
- Identify genes which have different expression patterns in different groups

Tools: Cluster Analysis, PCA and MDS

## Class Comparisons Example

- Find genes that are differentially expressed among cancer groups
- Find genes up/down regulated by drug treatment

- Tools:
  - Two or more group comparison
  - Statistics Results filtering

#### Class Prediction Example

- Identify an expression profile which correlates with survival in certain cancers
- Identify an expression profile which can be used to diagnose different types of lymphomas

• Tools: Prediction Analysis for Microarrays (PAM)

#### 3. mAdb dataset analysis tools

- Class Discovery: clustering, PCA, MDS
- Class Comparison: statistical analysis
- Class Prediction: PAM

#### **Class Discovery**

- Dataset with large amount of data
- Dataset not organized
- Visualization with Clustering, PCA, MDS

#### Cluster Analysis

- Organize large microarray dataset into meaningful structures
- Visualize and extract expression patterns

#### What to Cluster?

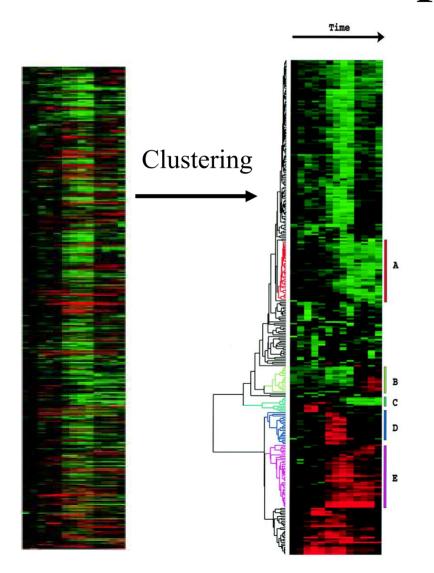
Genes - identify groups of genes that have correlated expression profiles

Samples - put samples into groups with similar overall gene expression profiles

## **Clustering Methods**

- Hierarchical clustering
- Partitional clustering
  - K-means
  - Self-Organizing Maps (SOM)

#### Cluster Example on Genes



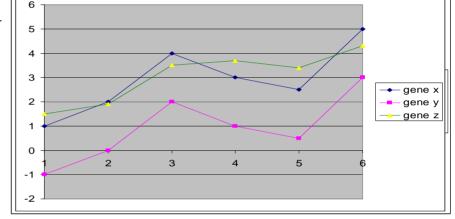
Much easier to look at large blocks of similarly expressed genes

Dendogram helps show how 'closely related' expression patterns are

- A. Cholesterol syn.
- B. Cell cycle
- C. Immediate-early response
- D. Signaling
- E. Tissue remodeling

#### 2 Steps

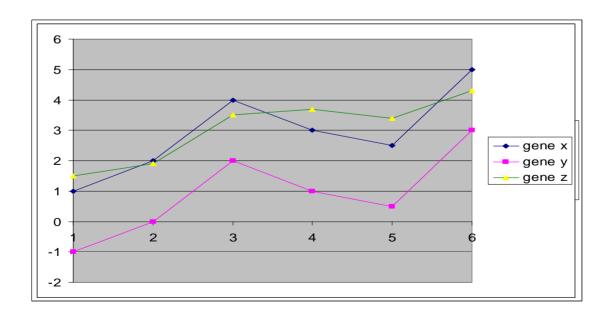
- Pick a distance method
  - Correlation
  - Euclidian



- Pick the linkage method
  - Average linkage
  - Complete linkage
  - Single linkage

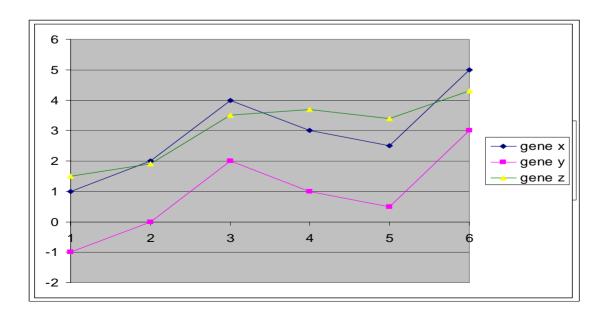
#### **Correlation**

- Compares shape of expression curves (-1 to 1)
- Can detect inverse relationships (absolute correlation)

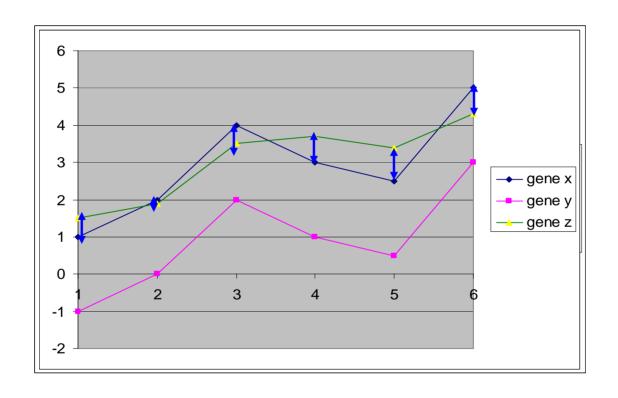


#### Two Flavors of correlation

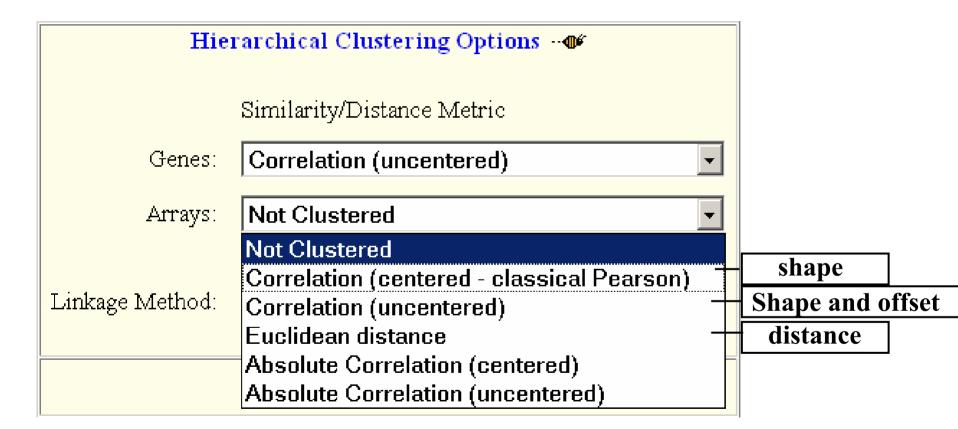
- Correlation (centered-classical Pearson)
- Correlation (un-centered)
  - assume the mean of the data is 0, penalize if not
  - Measures both similarity of shape and the offset from 0



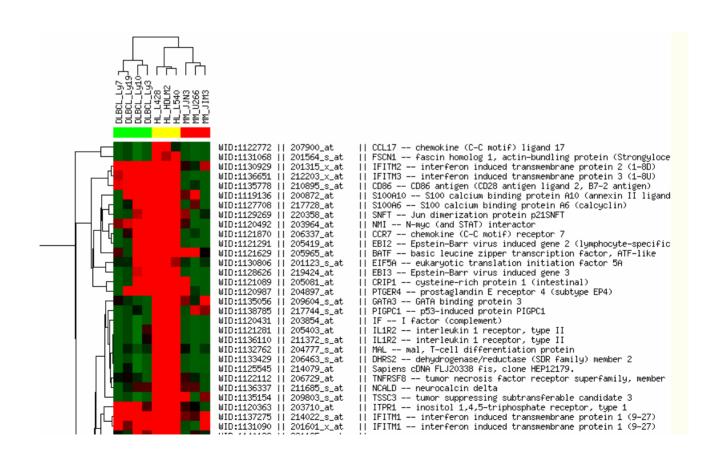
#### **Euclidean Distance**

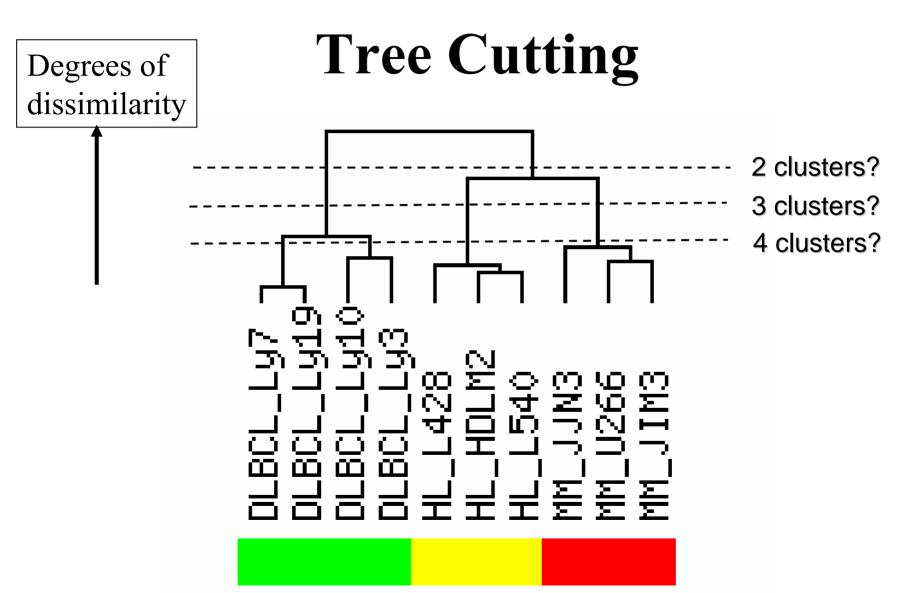


#### Similarity/Distance Metric Summary



#### Hierarchical Clustering Example





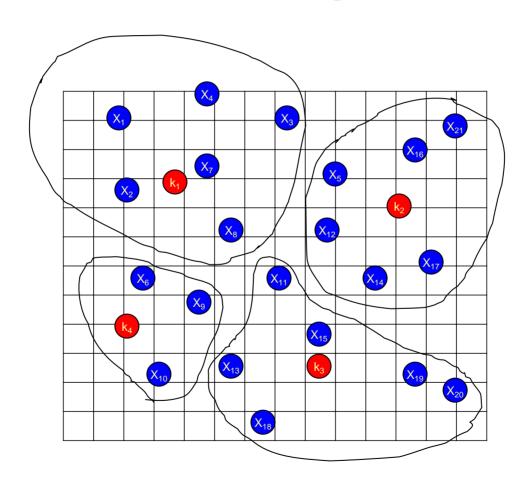
# **Hierarchical Clustering Summary**

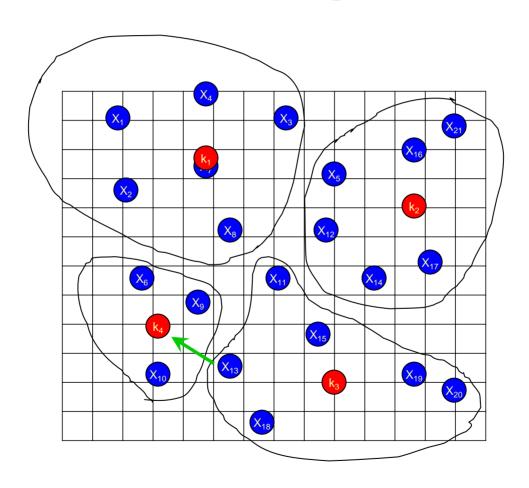
- Detection of patterns for both genes and samples
- Good visualization with tree graphs
- Dataset size limitations
- No partition in results, require tree cutting

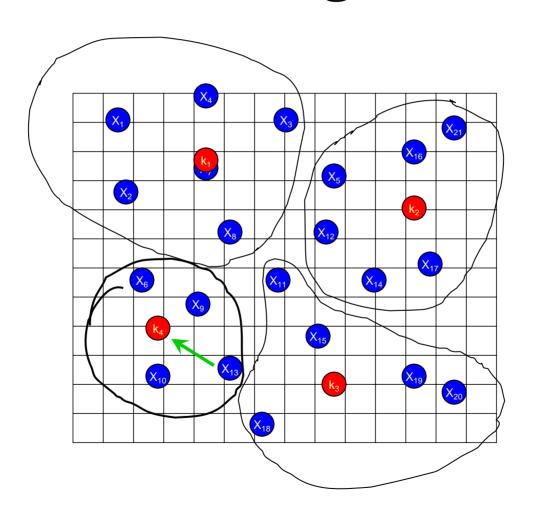
# Partitional clustering: K-means

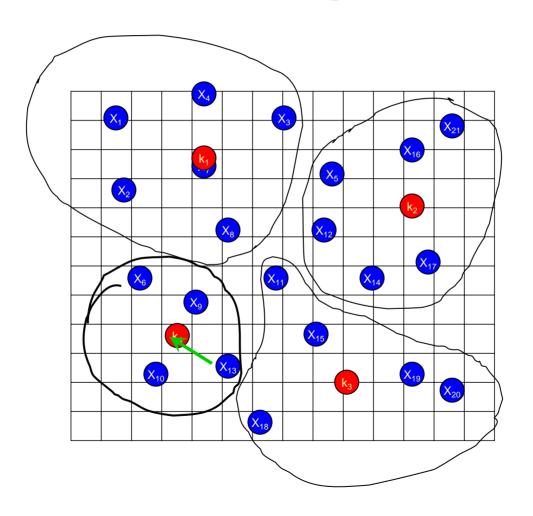
- Partition data into K clusters, with number K supplied by user.
- Produce cluster membership as results.

- Divide observations into K clusters.
- Use cluster averages (means) to represent clusters
- Maximize the inter-cluster distance Minimize intra-cluster distance.





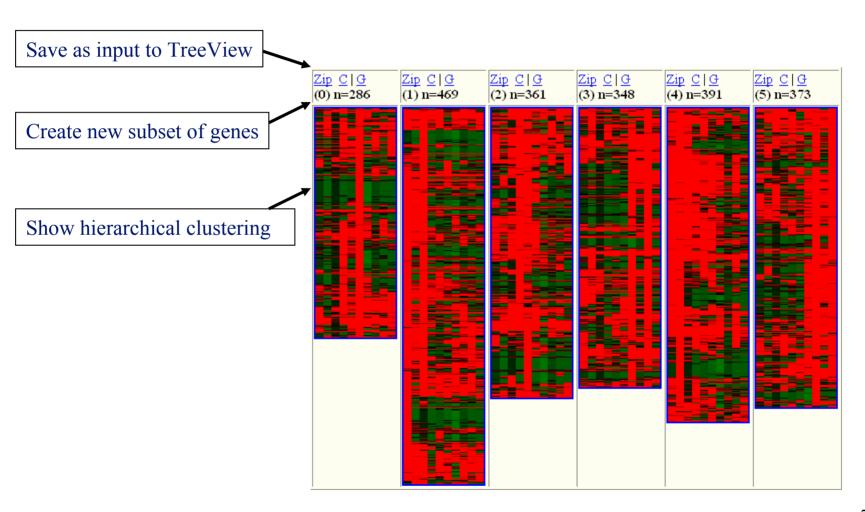




#### mAdb K-means Options

Kmeans Clustering Options -- 06 Specify Number of Nodes 5 Set number of clusters Maximum Number of iterations 100 Set number of iteration **Kmeans Nodes** Hierarchical Clustering Options -- 06 Similarity/Distance Metric Hierarchical clustering Correlation (uncentered) Genes: within node Not Clustered Arrays: Linkage Method: Average Linkage Cluster

#### K-means Clustering Example



#### Summary

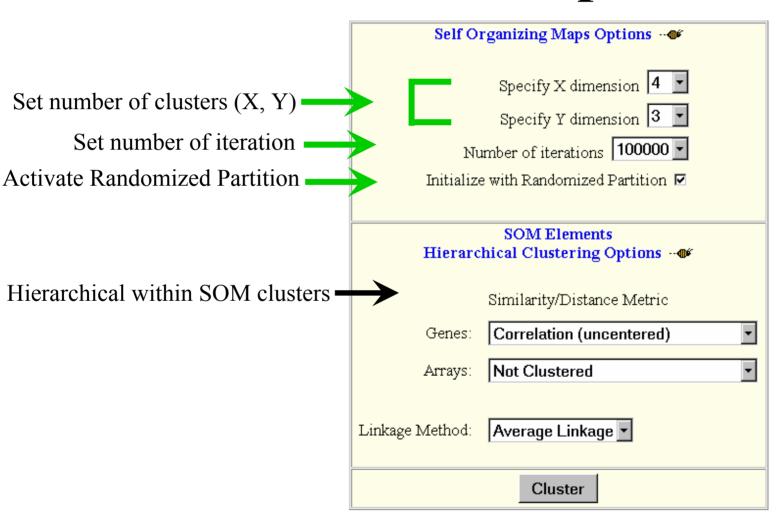
- Fast algorithm
- Partitions features into smaller, manageable groups
- mAdb allows hierarchical clustering within each K-mean cluster

- Must supply reasonable number of K
- No relationship among partitions

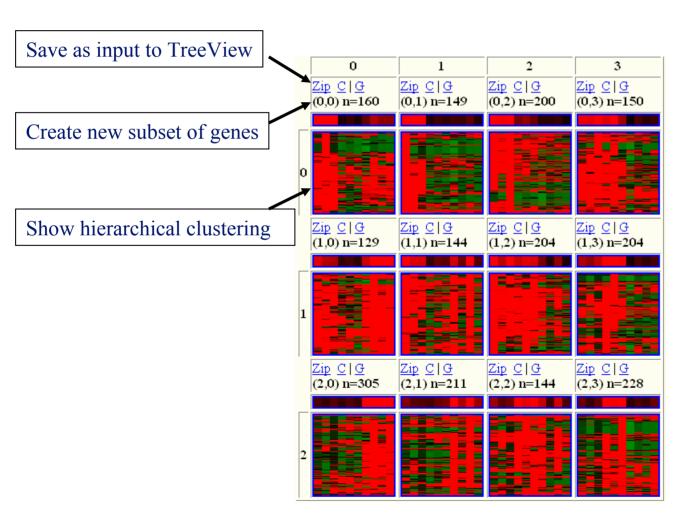
#### **Self-Organizing Maps (SOM)**

- Partitions data into 2 dimensional grid of nodes
- Clusters on the grid have topological relationships
- 2 numbers for the dimension of grid supplied by user

#### mAdb SOM options



# **SOM Clustering Example**



#### **SOM Summary**

- Neighboring partitions similar to each other
- Partitions features into smaller groups
- mAdb allows hierarchical clustering within each SOM cluster

Results may depend on initial partitions

#### **Summary of mAdb Clustering Tools**

	Hierarchical	K-means	SOM
Relationship visualization	Tree Structure	partition Membership	Partition 2-D topology
Data Size	Small	Large	Large
Performance	Slow	Fast	Middle
Cluster Type	Gene/Array	Gene	Gene

#### Cluster Analysis

- Normalization is important
- Reduce data points by variance
- Use K-mean or SOM to partition dataset
- Use biological information to interpret results

#### **Hands-on Session 2**

- Lab 5 lab 6 (Lab 7 optional)
- Total time: 15 minutes

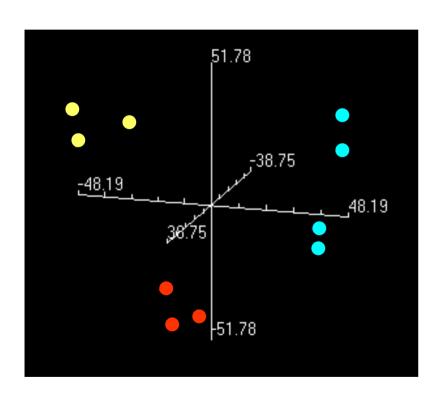
### Principal Component Analysis

- How different samples are from each other
- Project high-dimensional data into lower dimensions, which captures most of the variance
- Display data in 2D or 3D plot to reveal the data pattern

### Principal Component Analysis

- Hypothesis there exist unobservable or "hidden" variables (complex traits) which have given rise to the *correlation* among the observed objects (genes or microarrays or patients)
- The Principal Components (PC) Model is a straightforward model that seeks to achieve this objective

#### PCA 3D plot



- Axes represent the first 3 components
- The first 3 components should explain most of the variance
- Formation of clusters
- Relationship of clusters.

**Basic Idea of PCA** is a Data Reduction Method Based on Analysis of Correlation Pattern(s) That Can Exist Among the Observed Random Variables (i.e. Expression values of Genes).

Raw Data

Array	1	2	•••	m
Gene 1	$a_{11}$	$a_{12}$	•••	$a_{1m}$
Gene 2	$a_{21}$	$a_{22}$		$a_{2m}$
Gene	:	:	: :	:
Gene n	$a_{n1}$	$a_{n2}$		$a_{nm}$

n is the number of genes (gene probes); m is the number of arrays (experiments)

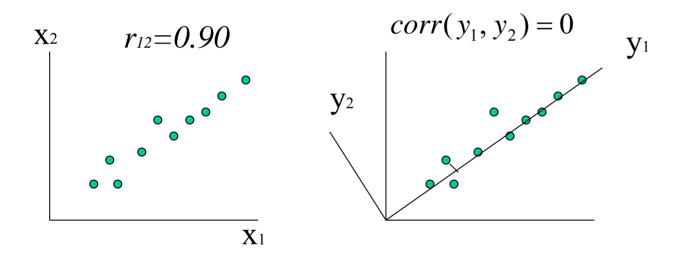
#### A Structure of Correlation Matrix is the Major Object for PCA

Correlation	Gene 1	Gene 2	•••	Gene n
Matrix				
Gene 1	1	$r_{12}$		$r_{1n}$
Gene 2	$r_{21}$	1		$r_{2n}$
Gene	:	:	:	:
Gene n	$r_{n1}$	$r_{n2}$		1

A correlation matrix is a symmetric matrix of correlation coefficients  $(-1 \le r_{ij} \le 1 \text{ and } r_{ij} = r_{ji}; i, j = 1, 2, ..., n; r_{ii} = 1)$ 

The Results of PCA are a small set of the orthogonal (independent) Variables Grouping of the Variables

From a purely mathematical viewpoint the purpose of PCA is to transform **n** correlated random variables to an orthogonal set which reproduces the original variance/covariance structure.

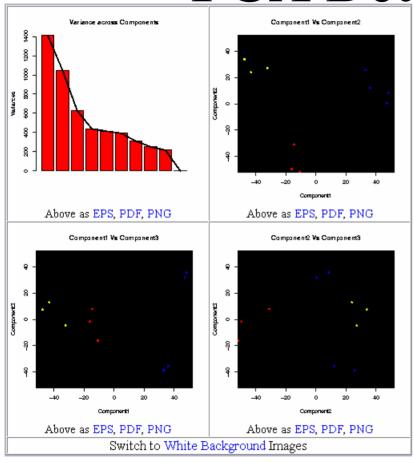


(The First) Principal Component y<sub>1</sub> can "explain" the major fraction (~90%) of a dispersion of variables x<sub>1</sub> and x<sub>2</sub> for all of the 10 observed objects.

#### Sample: Small Round Blue Cell **Tumors**

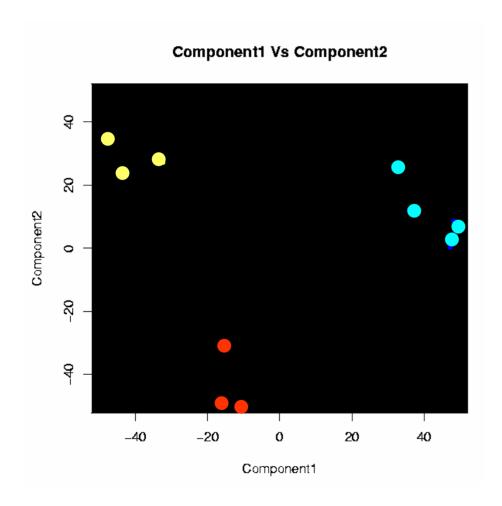
- 63 Arrays representing 4 groups
  - BL (Burkitt Lymphoma, n1=8)
  - EWS (Ewing, n2=23)
  - NB (neuroblastoma, n3=12)
  - RMS (rhabdomyosarcoma, n4=20)
- There are 2308 features (distinct gene probes)

#### **PCA Detailed Plot**



- "Scree" plot
- 2-D plots

# **PCA 2-D plots**



• First 2 components separate 3 groups well

# MDS overview (Multidimensional Scaling)

- An alternative for PCA
- Non-linear projection methodology
- Tolerates missing values

#### Summary of PCA and MDS

- Dimension reduction tools
- Graphic representation to help explain patterns
- Quality control for experimental variance

#### **Hands-on Session 3**

- Lab 8
- Total time: 15 minutes

• Next class tomorrow at 1:00 pm

#### Analyzing Microarray Data using the mAdb System

February 16-17, 2005 1:00 pm - 4:00pm madb-support@bimas.cit.nih.gov

Day 2

mAdb Analysis Tools

Esther Asaki, Liming Yang, John Powell

#### Agenda

- 1. mAdb system overview
- 2. mAdb dataset overview
- 3. mAdb analysis tools for dataset
  - Class Discovery clustering, PCA, MDS
  - Class Comparison statistical analysis
    - t-test
    - ANOVA
    - Significance Analysis of Microarrays SAM
  - Class Prediction PAM

Various Hands-on exercises

#### **Class Comparison**

- Statistical distributions of gene expression data
- Hypothesis test and two types of errors
- mAdb statistical analysis tools for class comparison
  - t-test
  - One way ANOVA
  - SAM

## **Concept of Probability**In Terms of Microarray Data

N: total number of measurements of the expression level of a gene,

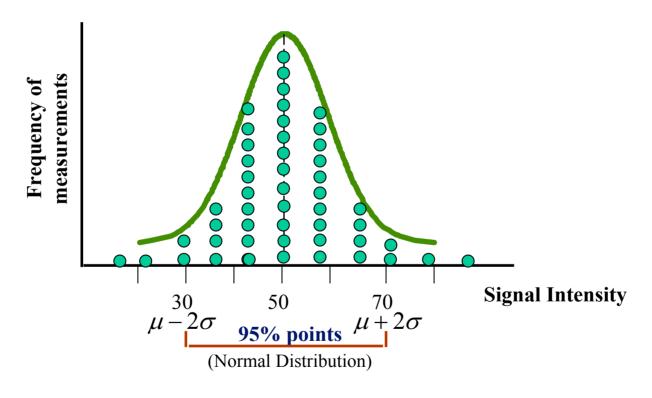
**n(A):** number of occurrence of expression level A,

**Probability**: the ratio n(A)/N approximates the probability of getting expression level A, P(A), with increasing accuracy as N increases.

$$P(A) \leftarrow n(A) / N, 0 \le P(A) \le 1$$

To get the probabilities of all possible expression levels of a gene, we can construct the **histogram** (the empirical frequency distribution), which approximates the **probability function** of the expression level of that gene.

## Replicated Measurements and the Frequency Distribution Function



Center: Mean μ Spread: Standard deviation σ

## Sources of Errors and Uncertainty in Microarray Data Analysis

- Poorly-controlled external factors (quality of tissue sample, RNA etc.)
- Mixture of biological samples derived from many cells and/or complex tissues
- Biological noise (stochastic mechanisms of gene expression)
- Technical noise of background signals
- Limited number of replicates (cost, personnel, etc. constraints)
- Inadequate statistical methods

#### **Technical Caveats**

- Technical variability (noise) has a significant intensity bias for low signal intensity values.
- Normalization is required for comparison.
- Simple, static fold change thresholds are too stringent at high intensities and not stringent enough at low intensities.

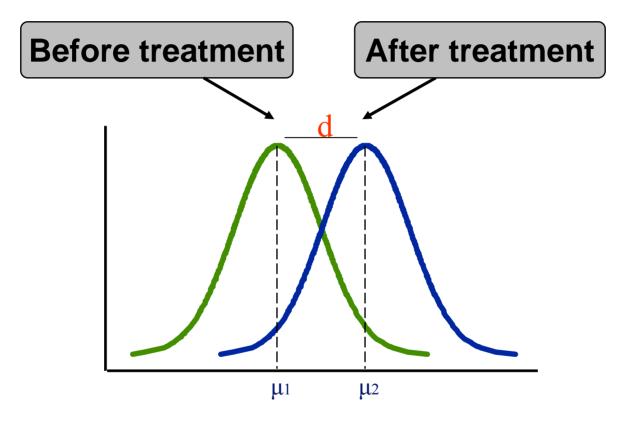
## Statistical and Biological Problems with Fold Change of Means

- Genes with high fold change may exhibit high variability among cell types due to natural biological variability for these genes
- Genes with small fold changes may be highly reproducible and should be biologically essential genes

#### **Conclusion**

Need robust statistical tests of microarray data Need additional biological validations

### **Hypothesis Test**



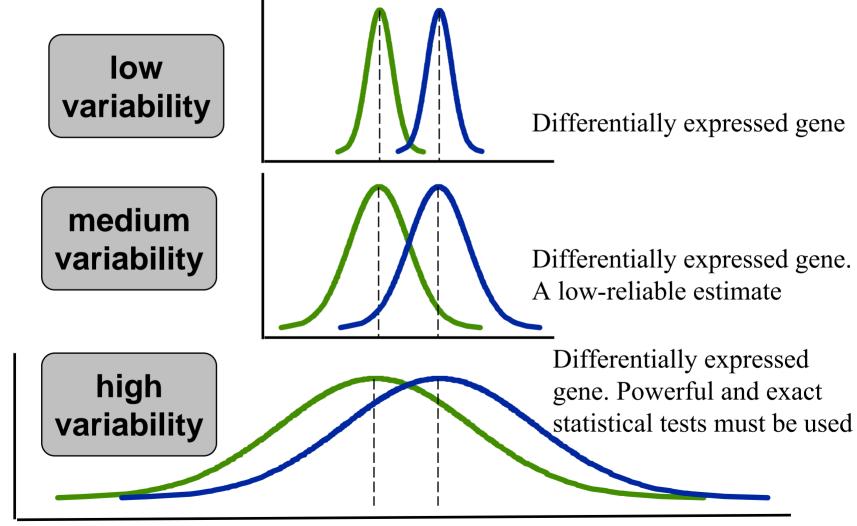
Null hypothesis  $H_0: \mu_1 = \mu_2$ 

$$H_0: \mu_1 = \mu_2$$

Alternative hypotheses  $H_1: \mu_1 \neq \mu_2$ 

$$H_1: \mu_1 \neq \mu_2$$

## Spread (Variability) of Measurements



#### Two Types of Errors

Type I error: Rejecting the null hypothesis while it's true;

A a a a set 11 a

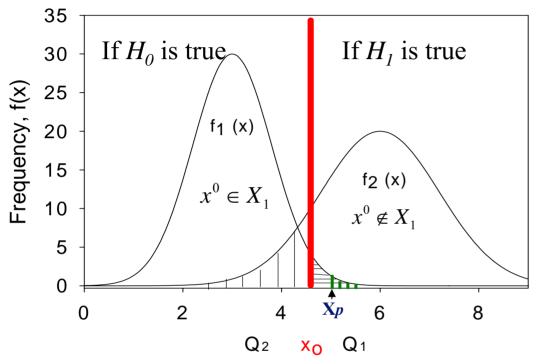
Type II error: Accepting the null hypothesis while it's not true.

	Accept Ho	Reject Ho
<i>Ho</i> is true	Correct decision	Type 1 error False positive
HO IS true		Taise positive
Ho is false	Type II error False negative	Correct decision
	raise negative	

Daiget IIa

81

## Relation of Type I & Type II Errors



 $X_1$ : data set for control population

 $X_2$ : data sets for tested population

 $x_0$ : the critical (the rejection) value of x

 $x^{o}$ : the observed value of x

Q<sub>1</sub>=The probability of a type I error (false-positive)

Q<sub>2</sub>=The probability of a type II error (false-negative)



Any modifications of  $x_0$  has the opposite effects on probabilities of errors of Type I and Type II: if  $Q_1$  is pushed down, then  $Q_2$  is raised. However, an increase of sample size decreases of both types of errors.

The *p-value* is the probability (significance value) at which a true null hypothesis is rejected *by chance only*.

82

### **Class Comparison**

**Goal:** To identify differentially expressed genes, i.e. a complete list of genes with expression levels statistically and (more important) biologically different in two or more sets of the representative transcriptomes.

• t-test (2 groups)

• ANOVA (> 2 groups)

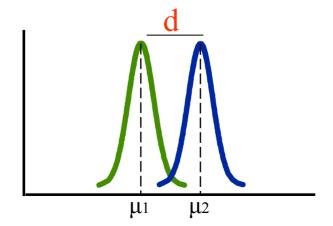
• SAM (1, 2, and more groups)

#### t-Test

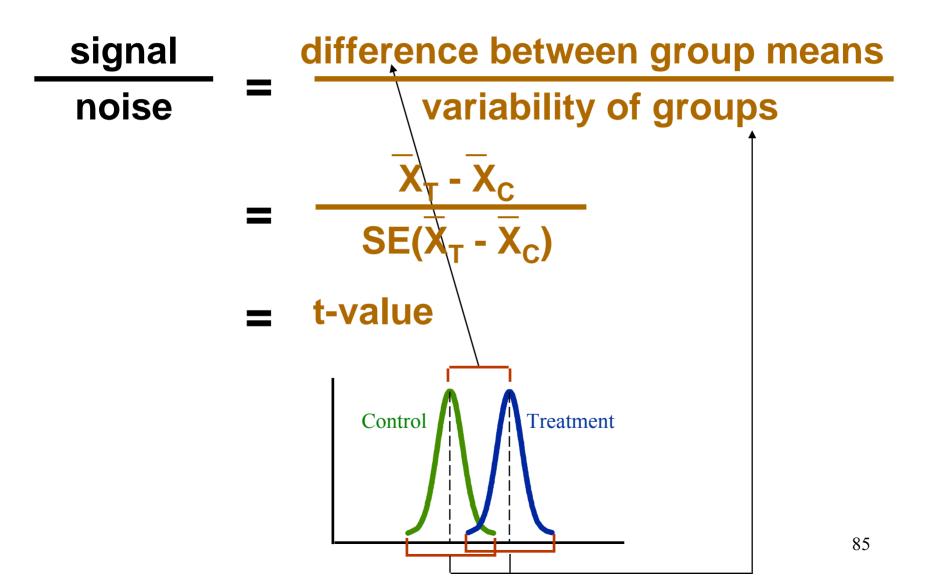
The t-test assesses whether the means of two groups are statistically different

The null hypothesis:

$$H_o: \mu_1 - \mu_2 = 0$$



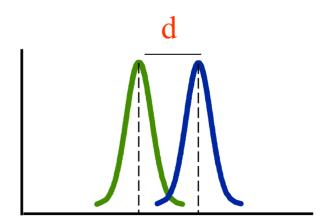
### t-Test (Cont'd)



### Calculating p-Value (t-Test)

- The p-value is the probability to reject the null hypothesis (  $H_o: \mu_1 \mu_2 = 0$  ) when it is true (e.g. p=0.0001)
- When carrying out a t-test, a p-value can be calculated based on t and the sample sizes  $n_1$  and  $n_2$ .

Large distance d,
low variability,
large sample sizes,
then small p,
i.e. more significant.



#### mAdb t-Test

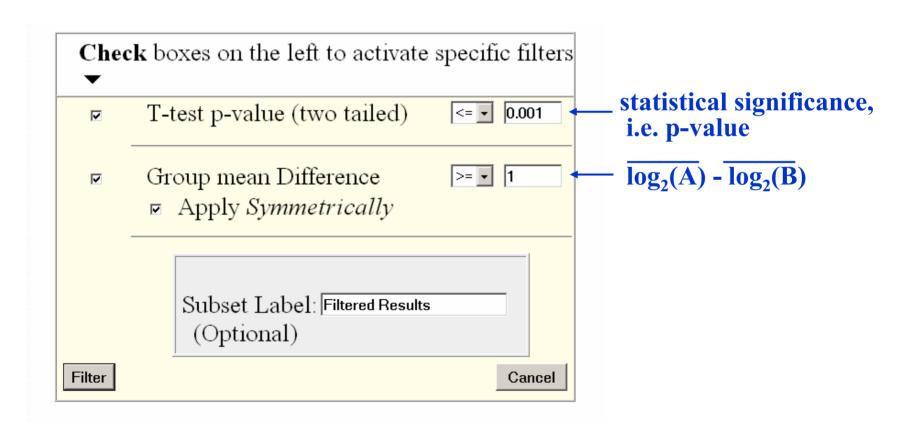
• 2 group statistic analysis automatically selected for a 2 group dataset

Statistical Group Analysis					
Two Group Comparison: t-test Separate (unequal) variance	•	<b>—</b>			
Dataset Properties					
Subset Label: t-test result					
Proceed					

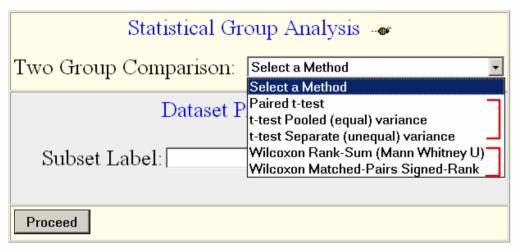
#### t-Test Results

B ● ● ● ●
10_A p-Value Difference
3532 1.9737e-06 6.07
3532 8.9006e-06 5.83
3532 1.1662e-05 6.24
0555 1.4619e-05 -0.72
3532 2.4704e-05 3.93
0657 3.7853e-05 -3.9
2551 4.7738e-05 -1.07
358 4.9127e-05 -1.77
5493 5.7477e-05 -3.51
3106 5.8369e-05 -3.35
9403 6.3509e-05 -6.28
3532 7.1258e-05 5.71
3532 8.4299e-05 -0.329
2176 9.1539e-05 -5.31
3532 9.9425e-05 1.88
9078 0.00014347 -4.91
3532 0.00014599 1.09

## Statistic Results Filtering



## Other Statistical Tests for 2 Group Comparison



**Parametric (normal distribution)** 

**Non-Parametric (distribution free)** 

#### Multiple Group Comparison

	Group 1	Group 2	•••	Group k
Gene 1	$\mu_{1.1}$	$\mu_{1.2}$	•••	$\mu_{1.k}$
Gene 2	μ <sub>2.1</sub>	μ <sub>2.2</sub>	•••	$\mu_{2.k}$
	•••	•••	•••	•••
Gene n	$\mu_{n.1}$	μ <sub>n.2</sub>	•••	$\mu_{n.k}$

n: Number of genes/probes

k: number of groups, k > 2

### Analysis of Variances (ANOVA)

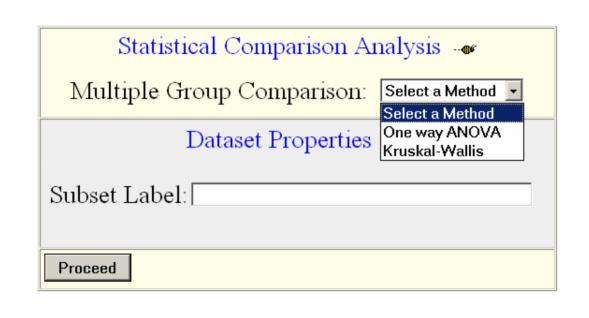
To compare several population means:

$$H_o: \mu_1 = \mu_2 = \dots = \mu_k \quad (k > 2)$$

VS.

$$H_1: \mu_i \neq \mu_j$$
; for some  $1 \le i \ne j \le k$ 

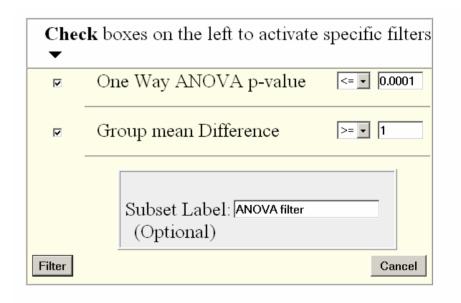
#### Multiple Group Comparison



- ANOVA: parametric test based on F-statistics
- Kruskal-Wallis: non-parametric rank-based test

#### **ANOVA Results and Filtering**

• •	• •	• •
p-Value	Difference	Groups
9.6276e-22	4.11	A-B
3.488e-20	2.99	D-C
2.5008e-19	3.59	A-B
2.5733e-18	2.59	A-D
1.4459e-17	2.76	D-A
5.7703e-17	2.89	A-B
8.728e-17	3.14	D-B
1.3957e-16	3.95	C-A
4.1114e-16	4.03	A-B
1.4464e-15	3.76	A-B
2.369e-15	3.1	D-B
7.4515e-15	3.32	A-B
8.187e-15	2.76	A-C
2.5078e-14	4.1	A-B
2.5526e-14	5.68	D-B



← Group Pair for Max Mean Difference

#### **Hands-on Session 4**

- Lab 9
- Total time: 15 minutes

## Multiple Testing

- Large-scale experiments & statistical problems
  - Finding the differentially expressed genes measured simultaneously in the two or more groups of microarrays has a problem of multiple comparison, where many null hypotheses are tested simultaneously.
- p-value adjustment
  - Although p-value cut off ( $\alpha$ ) of 0.01 is significant in a conventional single-variable test, a microarray experiment for 20,000 gene probes would identify 20,000 x 0.01 = 200 genes just by chance!

## **Correcting Multiple Testing**

- False Discovery Rate (FDR)
- Significance Analysis of Microarrays (SAM): Modified t-test for selection of the differentially expressed gene sets, and calculates FDR
- http://www-stat.stanford.edu/~tibs/SAM/index.html
- Estimation of the parameters of the model and their optimization
- Interpretation of SAM output and SAM plot

### Multiple Testing and FDR

	Not rejected	Rejected	Total
H <sub>0</sub> True	m <sub>0</sub> -V	V	$m_0$
H <sub>1</sub> True	m <sub>1</sub> -S	S	$\mathbf{m}_1$
Total	m-R	R	m

m: # hypothesis

V: # false positive

R: # significant hypothesis

Probability of false-positive gene discovery:

False Discovery Rate (FDR) = E(V/R|R>0) \* Pr(R)

# Significance Analysis of Microarrays (SAM)

- To select a fairly large number of differentially expressed genes, accepting some *falsely significant* genes, as long as their number is relatively small compared to the total number of significant genes, selected at significance level *a*.
- For one or two groups, SAM computes a t-like statistic d(i) for each probe i (i=1,2...n), measuring the difference between the normalized mean signals of the groups.
- For more groups, SAM computes a F-like statistic.

## SAM for 2 groups

I. The "relative difference" d(i) in gene expression for two groups I and U of repeated samples is:

$$d(i) = \frac{x_I(i) - x_U(i)}{s(i) + s_0}$$

 $x_I(i)$ : average expression level for gene *i* in group I,

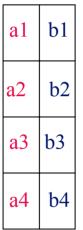
 $x_U(i)$ : average expression level for gene i in group U,

s(i): the estimate of standard deviation of repeated measurements,

 $s_o$ : the fudge factor that reduces the "relative differences" of the low expressed genes (noise) and/or genes with similar expression levels. i.e. d(i) will not be too large with small s(i).

## Permutations of the Arrays and the Expected Relative Differences

Group I Group U



Group I Group U

<u> </u>		-
b1	a1	
a2	b2	
a3	b3	
a4	b4	

Group I Group U

b1	a1
a2	b2
b3	a3
a4	b4

*n*: the number of hybridized signals (gene probes);

k: the number of permutations of arrays between the groups.

Permutation 1: 
$$d_1(1) \leq ... \leq d_1(n)$$

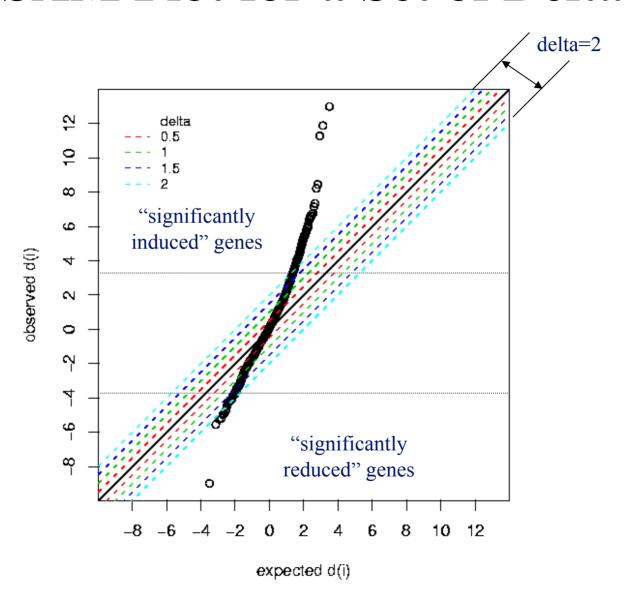
Permutation p: 
$$dp(1) \leq ... \leq dp(n)$$

Permutation k: 
$$d_k(1) \le ... \le d_k(n)$$

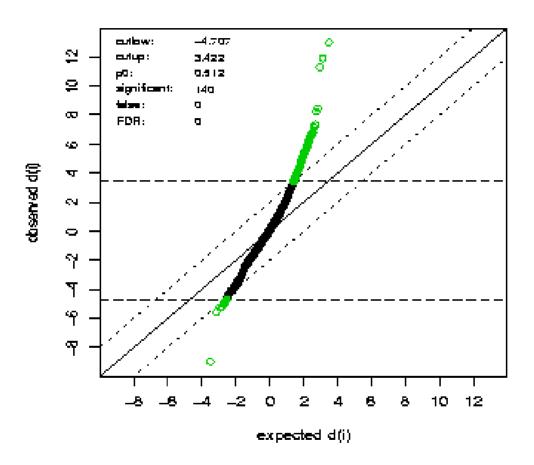
$$\bar{d}(i) = \frac{1}{k} \sum_{i=1}^{k} d_{p}(i)$$

Expected relative difference for gene 
$$i$$
 ( $i=1,2,...n$ )

#### SAM Plot for a Set of Delta



#### **SAM Plot for Delta = 2**



#### FDR estimation:

The ratio of average number of falsely significant gene probes exceeding a given cutoff value (delta) to the number of significance gene probes at that  $\operatorname{cutoff}_{103}$ 

#### mAdb SAM

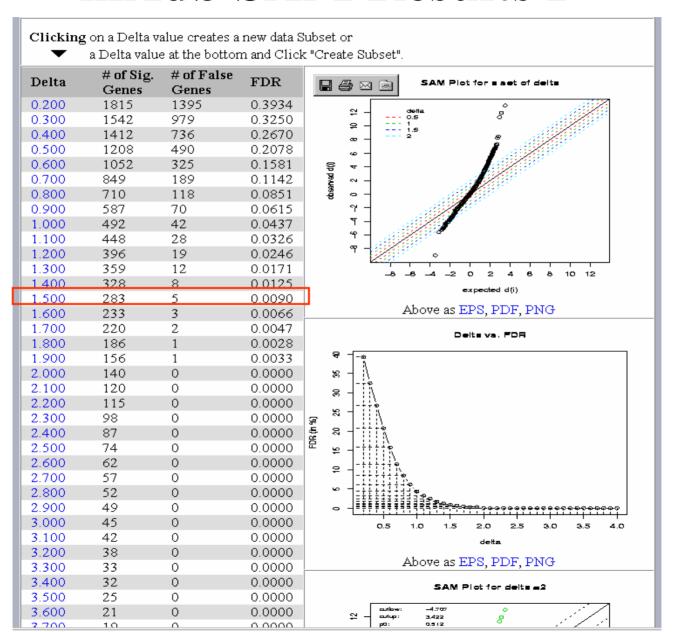
from Dataset: Small, Round Blue Cell Tumors (SRBCTs), Nature Medicine Vol 7, Num 6, 601-673 (2001) Interactive Array Filtering 88 arrays and 2308 genes in the original data set 11 arrays and 2308 genes in the output data set. 77 arrays were excluded by interactive grouping/filtering No arrays were restored by interactive grouping/filtering 6 arrays assigned to Group A 5 arrays assigned to Group B View the complete History. Expand this Dataset. Access Datasets in your Temporary area. Filtering/Grouping/Analysis Tools -- @ Choose a Tool BETA SAM: Significance Analysis of MicroArrays Proceed Interactive Graphical Viewers -- @ MDS: MultiDimensional Scaling View Choose a Viewer Dataset Retrieval & Display Options -- @ Dataset formatted for | Eisen Cluster | Retrieve Redisplay ☐ Show Array Details at the top of the page Contrast 1.568 Background Color - None to 25 genes Limiting display to ✓ Use Names in Column Heading Show Data Values ☐ Apply log2 transform ☑ Use Description in Column Heading ☑ Show Gene Symbols ☑ Show Map Information

## **SAM Data**

Records 1 to 25 of 2308 total records displayed.

A EWS-T1		A EWS-T3	A	A	A	ъ	_				l			
EWS-T1		EWS-T3	THE ICL IN A			В	В	В	В	В			• •	• •
	1.6547		EWS-14	EWS-T6	RMS-C10	BL-C5	BL-C6	BL-C7	BL-C8	BL-C1	Aver	Mx-Mn	Well ID	Feature 1
3.2025		3.2779	1.0060	2.7098	1.5410	0.2989	0.1856	0.1045	0.3178	0.1437	-0.5176	4.971	1080460	IMAGE:21
0.0681	0.0710	0.1160	0.1906	0.2367	0.0672	0.0839	0.1283	0.0994	0.0494	0.0563	-3.4113	2.260	1080461	IMAGE:25
1.0460	1.0409	0.8926	0.4302	0.3693	0.6689	1.0989	1.7574	0.2362	0.9711	1.0739	-0.3952	2.895	1080462	IMAGE:26
0.1243	0.0520	0.1014	0.1035	0.2190	1.1397	1.3145	1.3695	1.2625	1.2685	0.1198	-1.5803	4.719	1080463	IMAGE:22
0.4941	0.2045	0.2818	0.2984	0.3711	0.0401	0.3285	0.1284	0.1687	0.0573	0.3935	-2.3232	3.623	1080464	IMAGE:22
3.1207	2.1609	1.9773	1.6804	1.7800	0.5750	0.7530	0.5325	0.9698	1.0432	2.3396	0.4040	2.551	1080465	IMAGE:22
3.7106	2.4452	3.2590	5.8901	3.2376	6.1087	3.0222	4.8113	4.6305	3.7375	3.3334	1.9511	1.321	1080466	IMAGE:23
1.8416	1.1473	1.4106	0.2958	0.6769	0.5264	2.2284	1.1472	0.6647	0.5825	1.0947	-0.1413	2.913	1080467	IMAGE:23
1.2607	0.7371	0.9548	0.7381	0.8546	0.7117	1.4646	2.8207	2.2148	1.2009	2.2681	0.3010	1.987	1080468	IMAGE:24
2.9001	1.9989	2.0775	1.6610	0.6808	1.0343	2.0438	2.6476	1.4568	1.6544	1.8761	0.7663	2.091	1080469	IMAGE:25
4.0270	2.6131	4.8139	4.9105	4.5104	7.6119	4.3938	4.5243	5.8249	5.6817	4.6666	2.2404	1.542	1080470	IMAGE:31
1.0643	0.8541	0.4257	1.5866	0.6461	0.6720	0.5792	0.7810	0.8217	0.8692	1.3787	-0.2795	1.898	1080471	IMAGE:31
4.0651	4.7284	4.7120	9.4802	3.6433	7.4534	4.1207	5.1979	4.6583	6.1956	4.8565	2.3692	1.380	1080472	IMAGE:27
1.4730	2.4784	2.7548	0.1667	1.7957	1.1213	1.9109	1.5108	1.2601	0.5194	0.7753	0.2096	4.047	1080473	IMAGE:27
2.7932	1.5103	1.9162	1.1314	1.0375	0.2976	0.6045	0.5331	0.4699	0.5765	0.9937	-0.1845	3.230	1080474	IMAGE:27
0.4815	0.8961	1.2710	2.6361	0.3976	0.1707	0.3801	0.4887	0.3888	0.4765	0.2920	-0.9078	3.949	1080475	IMAGE:28
1.4482	0.4850	1.1331	0.8405	0.8846	1.0015	0.8015	0.9010	0.6565	0.6765	0.5780	-0.2897	1.578	1080476	IMAGE:29
3.3214	2.3431	2.4818	0.9928	1.5156	1.1450	1.4196	1.6072	2.7400	2.5685	3.7927	0.9986	1.934	1080477	IMAGE:34
0.7022	0.2531	2.0350	0.1239	1.2582	1.5526	0.9754	1.9857	2.0390	0.8393	0.6224	-0.2245	4.041	1080478	IMAGE:35
1.7260	1.7841	1.7340	0.5216	1.0114	0.3846	0.8591	1.2435	1.0625	0.5903	1.9728	0.0471	2.359	1080479	IMAGE:32
1.5136	1.0886	2.6863	0.9867	1.5428	2.0073	0.8364	0.8401	1.0302	0.4571	1.4035	0.2410	2.555	1080480	IMAGE:32
3.9255	5.9544	5.5842	4.8170	5.1313	6.1289	5.3582	4.2545	6.3473	6.3606	5.0796	2.4056	0.696	1080481	IMAGE:33
0.5296	0.5337	1.1332	0.6451	0.6248	0.4066	0.3915	0.4413	0.2791	0.1034	0.5852	-1.1521	3.454	1080482	IMAGE:33
3.9098	2.7007	4.6055	2.0627	4.4183	6.0772	3.4114	3.9238	5.0894	4.3511	4.7345	1.9864	1.559	1080483	IMAGE:34
3.7136	3.2339	2.2437	3.1900	2.1173	2.9153	4.1731	2.5854	4.0399	4.4925	4.8857	1.7230	1.206	1080484	IMAGE:34

#### mAdb SAM Results I



#### mAdb SAM Results II

SAM d statistics

(normalized distance) (lowest FDR) Records 1 to 25 of 283 total records displayed. A A в В В  $\mathbf{B}$ В A A A EWS-T1 EWS-T2 EWS-T3 EWS-T4 EWS-T6 RMS-C10 BL-C5 BL-C6 BL-C7 BL-C8 BL-C1 Aver Mx-Mnd(i) s(i) q-value R.difference 0.2986 0.2757 0.2607 0.4046 0.4103 2.1557 1.9916 1.7072 1.3449 2.4256 -0.4450 3.218 -8.9834 0.1900 0.00077 -2.49500.5752 0.4646 0.5121 0.2998 0.2031 1.1779 2.6250 3.2456 4.0725 2.5397 3.2127 0.1340 4.326 -5.5538 0.4058 0.00171 -2.74080.2785 0.2982 0.5336 0.3906 0.2064 3.1465 1.3678 0.8978 -0.5247 3.930 -5.2410 0.3496 0.00233 -2.2919 .5561 0.6398 0.6545 0.4830 0.5677 0.4885 0.4298 1.3266 2.1554 1.4731 1.3334 1.0776 -0.2524 2.326 -5.1946 0.1848 0.00233 -1.41520.2151 0.2423 0.3112 0.1954 0.3141 0.1790 0.7768 0.4494 0.7267 0.8581 1.1068 -1.3189 2.628 -4.9903 0.2460 0.00277 -1.6651 2.392 -4.9316 0.2391 0.00278 0.3648 0.3268 0.6515 0.4455 0.5171 1.1521 1.4527 1.4889 1.6262 0.8665 -0.5166 -1.6116 0.1844 0.2833 0.2713 0.3253 0.2585 0.0756 0.7904 0.9508 1.3086 1.3896 0.7992 -1.2101 4.200 -4.8040 0.3838 0.00315 -2.2651 0.6507 0.0840 0.1838 0.3586 0.3173 0.43421 1608 1 6185 3 7828 2.5348 3.2213 -0.4652 5.493 -4.7068 0.5499 0.00327 -3.0012 0.0860 0.1757 0.1148 0.1902 0.2746 0.0852 1.5769 1.2605 2.0804 1.9797 0.2545 -1.4477 4.610 -4.4672 0.5933 0.00476 -3.0423 0.3246 0.3545 0.2067 0.0578 0.2635 0.1197 0.9197 1.1204 0.9938 1.0349 0.8334 -1.3339 4.277 -4.3639 0.4576 0.00515 -2.37970.4628 0.5709 0.4914 0.7941 0.3252 0.3888 1.7641 1.2860 1.5374 1.2258 0.9175 -0.3900 2.440 -4.2811 0.2482 0.00568 -1.43791.5096 0.8966 1.2869 0.7250 2.255 -4.2585 0.2450 0.00578 1.5115 0.7268 2.7377 3.1414 2.2796 2.6268 3.4603 0.7227 -1.4168 0.3846 0.2843 0.4020 0.2550 0.3152 0.1679 0.4970 0.8778 0.8845 1.3243 1.1308 -1.0464 2.980 -4.1966 0.3003 0.00602 -1.6283 0.1647 0.0735 0.1826 0.1091 0.1377 0.0525 0.6268 0.3213 0.3043 0.5631 0.3504 -2.3181 3.578 -4.1629 0.3722 0.00602 -1.91430.3863 0.6338 0.3197 0.1897 0.2734 0.0423 3.7478 2.2453 1.8450 1.3306 1.4104 -0.6948 6.469 -4.1253 0.6535 0.00602 -3.05750.3109 0.6175 0.3248 0.1131 0.4431 0.1240 1.1211 1.0641 1.4479 1.9277 4.4673 -0.6763 5.304 -4.1116 0.5612 0.00602 -2.6679 0.7987 0.3257 0.8323 0.4872 0.2898 3 9015 5.5857 4.5178 5.6381 5.8817 4.8603 0.8111 4.343 -4.1068 0.6207 0.00602 -2.9092 0.2239 0.3721 0.4905 0.3745 0.1621 0.4997 0.7104 1.2036 1.0815 1.1202 1.1465 -0.8553 2.892 -4.0817 0.3188 0.00602 -1.6589 0.5043 0.8385 0.5527 0.8775 0.3906 0.5454 1.5849 1.4227 2.2138 1.7559 1.0650 -0.1176 2.503 -4.0574 0.2567 0.00619 -1.3973 0.5589 0.3437 0.3238 2.2569 3.2467 -0.4025 3.385 -4.0029 0.3842 0.00655 0.41600.6563 0.31070.8792 0.9426 1.4504 -1.8888 0.7256 0.7514 0.5969 0.3064 0.4322 2.771 -3.9296 0.3036 -1.5376 0.9539 2.0728 1.4237 1.2331 1.8964 2.0909 -0.0685 0.0071 0.2113 0.1568 0.3634 0.21710.1918 0.1631 0.6020 0.4455 0.8289 0.5404 0.3778 -1.6400 2.402 -3.9028 0.2635 0.0071 -1.37070.5048 0.1327 0.5114 0.2240 0.6995 0.0670 4.8524 5.0288 4.1432 1.8065 0.7500 -0.3949 6.230 -3.9009 0.7650 0.0071 -3.3264 0.9880 0.3495 0.3034 0.3344 0.2990 1.4124 1.1339 2.0510 1.2561 2.1298 -0.3534 2.833 -3.8825 0.3753 0.00712 -1.79760.1427 -2.5841 0.8795 0.1936 0.2207 0.9624 3.5737 2.2461 2.4018 2.3751 1.5855 -0.1732 4.646 -3.8567 0.5823 0.00748

Significance value

#### **Hands-on Session 5**

- Lab 10
- Total time: 15 minutes

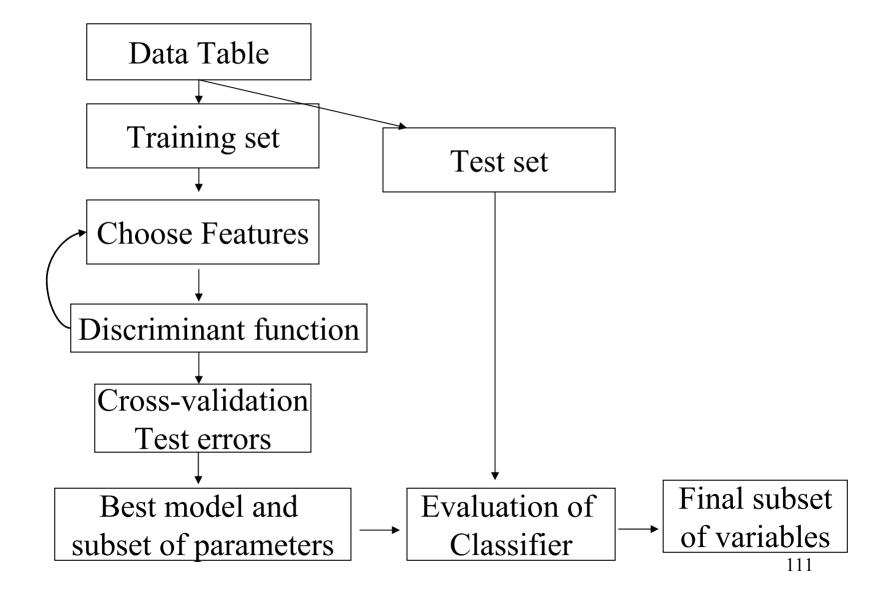
## 3. mAdb dataset analysis tools

- Class Discovery: clustering, PCA, MDS
- Class Comparison: statistical analysis
- Class Prediction: PAM

## Class Prediction Supervised Model for Two or More Classes

- Prediction Analysis for Microarrays (PAM)
- http://www-stat.stanford.edu/~tibs/PAM
- Provides a list of significant genes whose expression characterizes each class
- Estimates prediction error via cross-validation
- Imputes missing values in dataset

#### Design of the PAM algorithm



#### Calculating the Discriminant Function

For each gene, a centroid (sample mean) is calculated for each class.

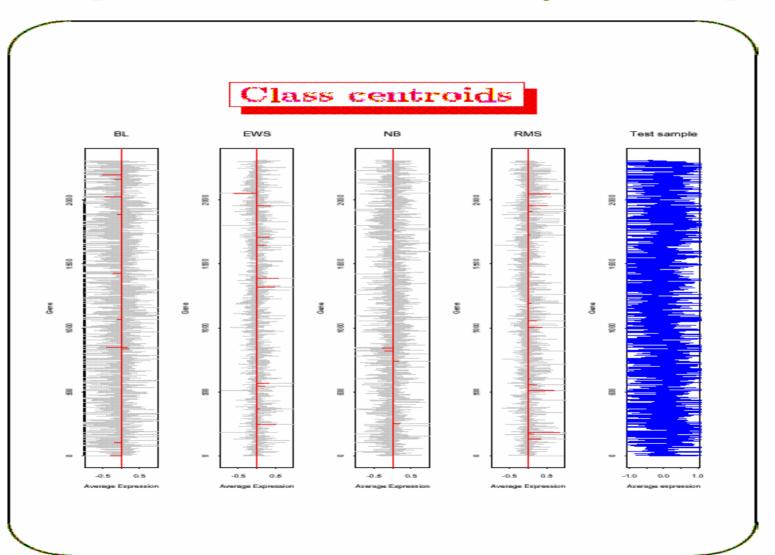
Standardized centroid distance are calculated: the average gene expression value in each class minus the overall gene expression average value, divided by the standard deviation-like normalization factor (NF) for that gene.

centroid distance= (class avg – overall avg) / NF

Creates a normalized average gene expression profile for each class

#### **Class Centroids**

SL&DM @Hastie & Tibshirani March 26, 2002 Supervised Learning: 31



#### Classifying an Unknown Sample

A classifier takes the gene expression profile of a new sample (microarray) from test sets, and compares it to each of these class centroids. The class whose centroid that it is closest to, in squared distance, is the predicted class for that new sample.

### K-fold Cross Validation

•The samples are divided up at random into K roughly equally sized parts.

**Entire Data Set** 

50 Group A

25 Group B

25 Group C

1

10 Group A

5 Group B

5 Group C

2

10 Group A

5 Group B

5 Group C

3

10 Group A

5 Group B

5 Group C

4

10 Group A

5 Group B

5 Group C

5

10 Group A

5 Group B

5 Group C

<del>115</del>

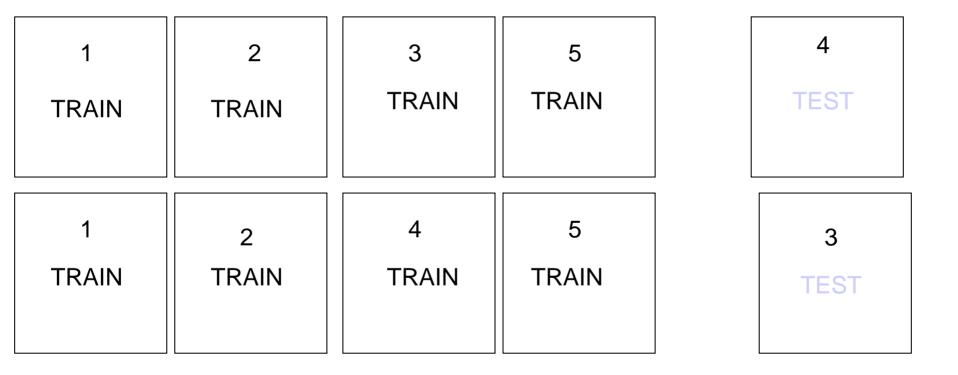
## **K-fold Cross Validation**

For each part in turn, the classifier is built on the other K-1 parts then tested on the remaining part.

1 2 3 4
TRAIN TRAIN TRAIN TRAIN

5 TEST

### **K-fold Cross Validation**



etc....

117

## **Estimating Misclassification Error**

• PAM estimates the predicted error rate based on misclassification error, which is calculated by averaging the errors from each of the cross validations.

• The model with lowest Misclassification Error is preferred.

## Reducing the Feature Set

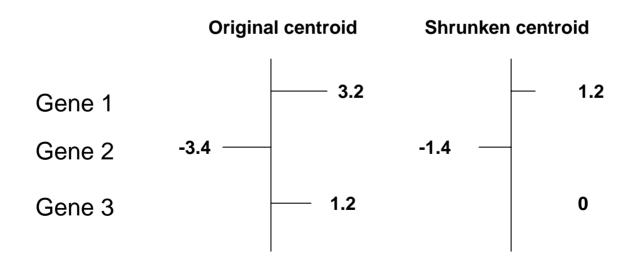
Nearest shrunken centroid classification makes one important modification to standard nearest centroid classification. It "shrinks" each of the class centroids toward the overall centroid for all classes by an amount we call the threshold. This shrinkage consists of moving the centroid towards zero by threshold, setting it equal to zero if it hits zero.

After shrinking the centroids, the new sample is classified by the usual nearest centroid rule, but using the shrunken class centroids.

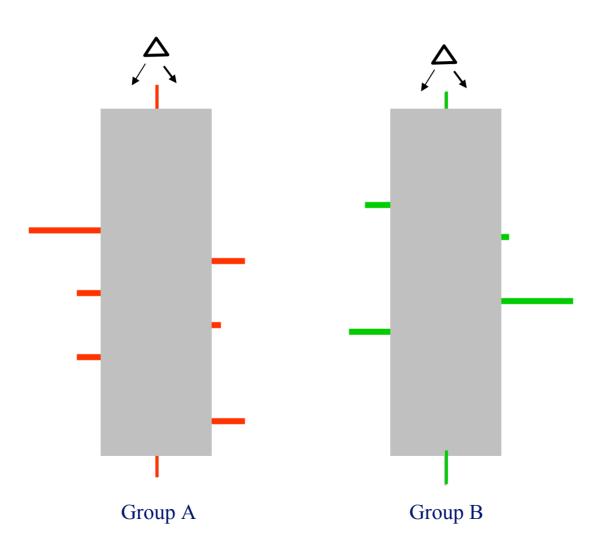
## Shrinking the centroid

Threshold = 2.0:

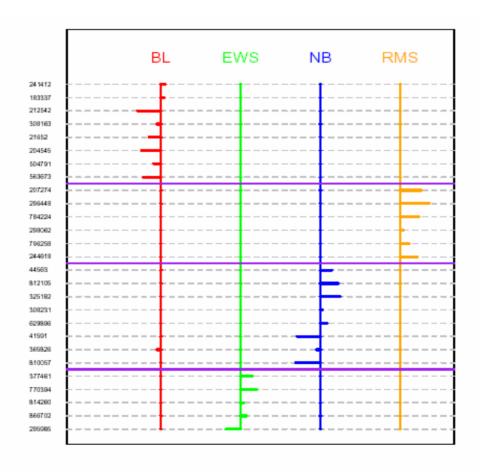
a centroid of 3.2 would be shrunk to 1.2; a centroid of -3.4 would be shrunk to -1.4; and a centroid of 1.2 would be shrunk to 0.



## Reduce Gene Number

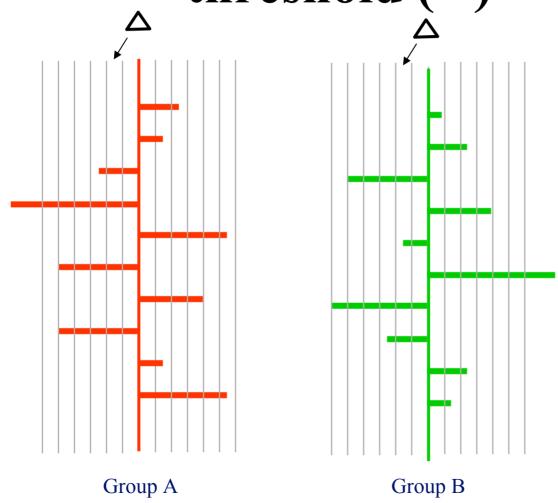


## **Prediction Model for SRBCT**



• Compare model with new tumor tissues to make diagnosis

# Multiple models with incremental threshold (\( \triangle \))



## Sample

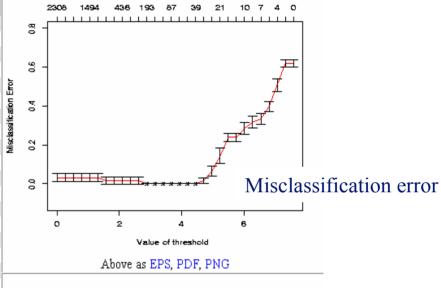
- 63 Arrays representing 4 groups
  - BL (Burkitt Lymphoma, n1=8)
  - -EWS (Ewing, n2=23)
  - NB (neuroblastoma, n3=12)
  - RMS (rhabdomyosarcoma, n4=20)
- There are 2308 features (distinct gene probes)
- No missing values in array data sets
- Each group has an aggregate expression profile
- An unknown can be compared to each tumor class profile to predict which class it most likely belong

## **PAM Results**

Clicking on a Delta value creates a new data Subset or enter

▼ a Delta value at the bottom and Click "Create Subset".

Shrinkage	# of	Misclass.
Delta	Genes	Error
0.000	2308	0.032
0.262	2289	0.032
0.524	2145	0.032
0.786	1878	0.032
1.048	1494	0.032
1.309	1137	0.032
1.571	853	0.016
1.833	609	0.016
2.095	436	0.016
2.357	330	0.016
2.619	244	0.016
2.881 **	193	0.000
3.143 **	151	0.000
3.404 **	107	0.000
3.666 **	87	0.000
3.928 **	68	0.000
4.190 **	52	0.000
4.452 **	39	0.000
4.714	32	0.016
4.976	23	0.063
5.238	21	0.143
5.499	16	0.238
5.761	11	0.238
6.023	10	0.286
6.285	9	0.317
6.547	7	0.333
6.809	5	0.397
7.071	4	0.508

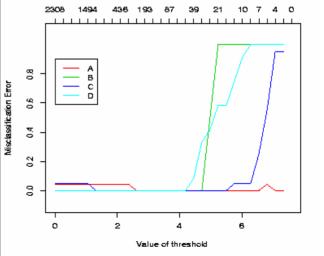


Create new model by fill in a new Delta value ---

Link leads to the dataset

with PAM model

Create Subset



## mAdb PAM Model

• •	• •	• •	• •
A Score	<b>B</b> Score	C Score	D Score
0.6092	-0.0866	0.0000	0.0000
0.0000	0.0000	0.0000	0.5862
-0.0696	0.0000	0.0000	0.5764
-0.5421	0.0000	0.0000	0.0000
0.5338	0.0000	0.0000	0.0000
0.0000	-0.5321	0.0000	0.0000
0.0000	0.0000	0.0000	0.4936
0.0000	-0.4873	0.0000	0.0000
0.0000	0.0000	0.0000	0.4821
0.0000	-0.4661	0.0000	0.0000
0.4380	0.0000	0.0000	0.0000
-0.0110	0.0000	0.0000	0.4269
0.0000	-0.4153	0.0000	0.0000
0.4086	0.0000	0.0000	0.0000
0.0000	0.0000	-0.3828	0.0000
0.3346	0.0000	0.0000	0.0000

## PAM summary

- It generates models (classifiers) from microarray data with phenotype information
- It does automatic gene selection for each models.
- Misclassification errors are calculated with the data for model selection.
- Require adequate numbers of samples in each group

## Hands-on Session 6

- Lab 11, Lab 12 (optional)
- Total time: 15 minutes

#### mAdb Development and Support Team:

- John Powell, Chief, BIMAS, CIT
- Liming Yang, Ph.D
- Jim Tomlin

- Esther Asaki\*
- Yiwen He, Ph.D.\*
- Kathleen Meyer\*
- Tim Ruppert\*

#### \*SRA International contractor









http://madb.nci.nih.gov http://madb.niaid.nih.gov

For assistance, remember:

madb\_support@bimas.cit.nih.gov

